



# Preparing microdata for public use: Confidentialization and disclosure control

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# Confidentialization and disclosure control: Outline

Intro

Risk and Utility Assessment

Types of Data Treatments

IPUMS Treatments: Sampling, Suppression, Swapping

Codeshare Demo

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# Confidentialization and disclosure control:

## Intro

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Codeshare Demo

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## THE CHALLENGE OF DATA PROTECTION

**DATA  
UTILITY**



**DATA  
SAFETY**

Huge research potential  
Better planning

**Data data everywhere**

Data to combine “disclosive”

Make the data accessible

**Good data stewardship**

Protect privacy

More solution options

**Technology**


Solutions in search of problems

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**CHALLENGES:  
DATA PROTECTION**

**FIVE SAFES FRAMEWORK**




Safe projects

Safe people

Safe data

Safe settings

Safe output



Is this use of the data appropriate, lawful, ethical and sensible?

Can the user be trusted to use data in an appropriate manner?

Does the data itself contain sufficient information for a potential confidentiality breach?


Does the access facility limit unauthorized use or mistakes?

Is the confidentiality maintained for the outputs by the data management system?

<https://blog.ons.gov.uk/2017/01/27/the-five-safes-data-privacy-at-ons/>  
<https://www.abs.gov.au/about/data-services/data-confidentiality-guide/five-safes-framework>

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## Confidentialization and disclosure control: What is confidentialization

- Confidentialization is the process of balancing utility and privacy

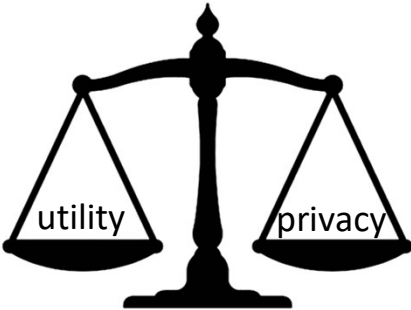
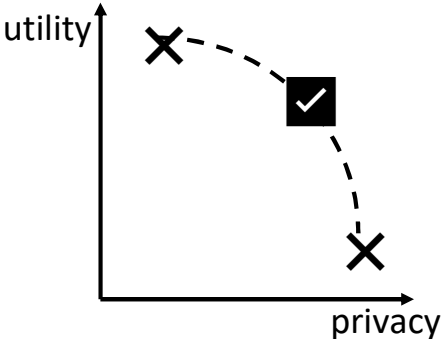


Image:  
www.needpix.com



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## Confidentialization and disclosure control: Assessing utility and risk

Utility
Useful <i>for what purpose?</i>

Risk
<i>How</i> might disclosure occur?
<i>What</i> might be disclosed?

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## Confidentialization and disclosure control: Useful for what purpose?

name	address	age	sex	marst	relate
John Doe	123 Main St.	30	male	married	head
Jane Doe	123 Main St.	30	female	married	spouse
Jack Doe	123 Main St.	4	male	NA	child
Jill Doe	123 Main St.	2	female	NA	child

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## Confidentialization and disclosure control: Useful for what purpose?

name	address	age	sex	marst	relate
		30	male	married	head
		30	female	married	spouse
		4	male	NA	child
		2	female	NA	child

## Confidentialization and disclosure control: Useful for what purpose?

id	name	address	age	sex	marst	relate
531	John Doe	123 Main St.	30	male	married	head
532	Jane Doe	123 Main St.	30	female	married	spouse
533	Jack Doe	123 Main St.	4	male	NA	child
534	Jill Doe	123 Main St.	2	female	NA	child

## Confidentialization and disclosure control: Useful for what purpose?

id	name	address	age	sex	marst	relate
531			30	male	married	head
532			30	female	married	spouse
533			4	male	NA	child
534			2	female	NA	child

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## Confidentialization and disclosure control: How might disclosure occur?

region	prov	age	sex	marst	relate	birthplace	occ	educ
3	2	30	male	married	head	San Jose	teacher	Master's
...	...	30	female	married	spouse	...	...	...
...	...	4	male	NA	child	...	...	...
...	...	2	female	NA	child	...	...	...

"KEY" ←

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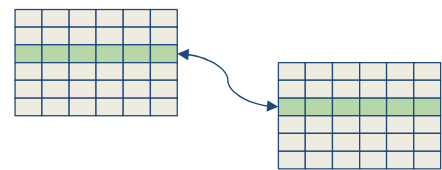
## Confidentialization and disclosure control: **How** might disclosure occur?

The “nosy neighbor”  
scenario



Image: www.vectorstock.com

The external  
archive scenario



Source: Dupriez and Boyko 2010, page 33

## Confidentialization and disclosure control: **What** might be disclosed?

region	prov	age	sex	marst	relate	birthplace	occ	educ	income
3	2	30	male	married	head	San Jose	teacher	Master's	\$40,000
...	...	30	female	married	spouse	...	...	...	...
...	...	4	male	NA	child	...	...	...	...
...	...	2	female	NA	child	...	...	...	...

## Confidentialization and disclosure control:

Intro

**Risk and Utility Assessment**

Types of Data Treatments

IPUMS Treatments: Sampling, Suppression, Swapping

Codeshare Demo

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## Confidentialization and disclosure control: Risk and Utility Assessment

Apply treatments:

Make data safer

Retain utility

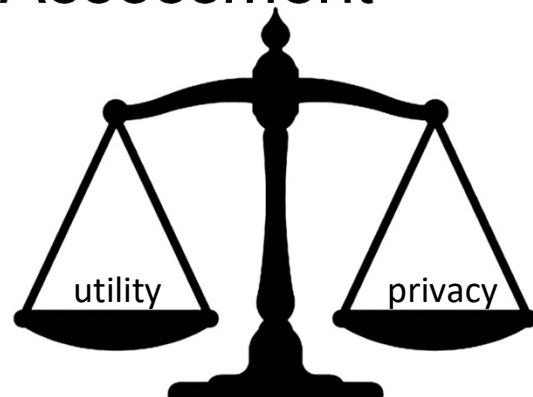


Image:  
[www.needpix.com](http://www.needpix.com)

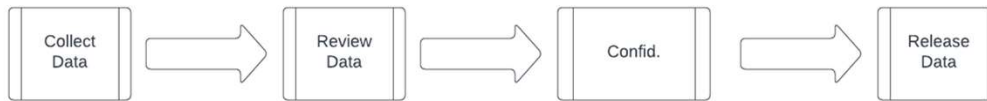
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# Confidentialization and disclosure control: Risk and Utility Assessment

- Within data production framework



# Confidentialization and disclosure control: Risk Assessment

- Highly Context dependent
- Can occur at different levels, at different times in the project
- Can be informal or formal assessments

## Confidentialization and disclosure control: Risk Assessment

- Highly Context dependent
- Can occur at different levels, at different times in data life cycle
- Can be informal or formal assessments

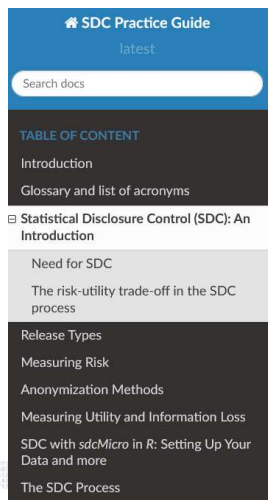
## Confidentialization and disclosure control: Risk Assessment

- Informal
  - Is this data likely to be targeted?
  - Does this data contain any sensitive questions?
  - Sensitive responses (EG, ethnic minorities)
  - Do certain combinations of variables pose a risk
    - EG, ethnic minority in a specific geographic unit

# Confidentialization and disclosure control: Risk Assessment

- Formal
  - *k-anonymity, l-diversity, t-closeness; in general:*
    - These methods all center around detecting unique records and how easy it is to individuate records.
  - In practice, these metrics can be complicated to calculate and easily skewed by large number of responses and/or variables.
    - Do not detect noise/confusion or other
    - Does a unique record in a sample represent the same risk as a unique records in the population?

# Confidentialization and disclosure control: Risk Assessment



SDC Practice Guide  
latest

Search docs

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  - Need for SDC
    - The risk-utility trade-off in the SDC process
  - Release Types
  - Measuring Risk
  - Anonymization Methods
  - Measuring Utility and Information Loss
  - SDC with *sdcMicro* in R: Setting Up Your Data and more
  - The SDC Process

Docs » Statistical Disclosure Control (SDC): An Introduction

[Edit on GitHub](#)

## Statistical Disclosure Control (SDC): An Introduction

### Need for SDC

A large part of the data collected by statistical agencies cannot be published directly due to privacy and confidentiality concerns. These concerns are both of legal and ethical nature. SDC seeks to treat and alter the data so that the data can be published or released without revealing the confidential information it contains, while, at the same time, limit information loss due to the anonymization of the data. In this guide, we discuss only disclosure control for microdata. <sup>[1]</sup> Microdata are datasets that provide information on a set of variables for each individual respondent. Respondents can be natural persons, but also legal entities such as companies.

The aim of anonymizing microdata is to transform the datasets to achieve an "acceptable level" of disclosure risk. The level of acceptability of disclosure risk and the need for anonymization are usually at the discretion of the data producer and guided by legislation. These are formulated in the dissemination policies and programs of the data providers and based on considerations including

**SDC Micro**

Risk  
assessment  
tool

# Confidentialization and disclosure control: Utility Assessment

- Narrow utility
  - Easy for small handful of tests, but unreasonable to know EVERY analysis the public might do
  - Useful to spot-check common cross-tabs (EG: SEX by Geog)
- Broad Utility
  - Not trying to match a specific metric, more concerned with the structure of dataset as a whole
  - a. Can get complicated as many data treatments alter class of the data

## CHALLENGES: DATA PROTECTION

### FIVE SAFES FRAMEWORK



Safe  
projects

Is this use of the data appropriate, lawful, ethical and sensible?



Safe  
people

Can the user be trusted to use data in an appropriate manner?

Safe data

Does the data itself contain sufficient information for a potential confidentiality breach?

Safe  
settings

Does the access facility limit unauthorized use or mistakes?

Safe  
output

Is the confidentiality maintained for the outputs by the data management system?

<https://blog.ons.gov.uk/2017/01/27/the-five-safes-data-privacy-at-ons/>

<https://www.abs.gov.au/about/data-services/data-confidentiality-guide/five-safes-framework>



# CHALLENGES: DATA PROTECTION

## FIVE SAFES FRAMEWORK

Projects – People – Data – Settings – Output



# CHALLENGES: DATA PROTECTION

## • FIVE SAFES FRAMEWORK

• Projects – People – Data – Settings – Outputs

DATA SAFETY



DATA UTILITY

Very safe

Not safe  
or unknown

### Toy data model

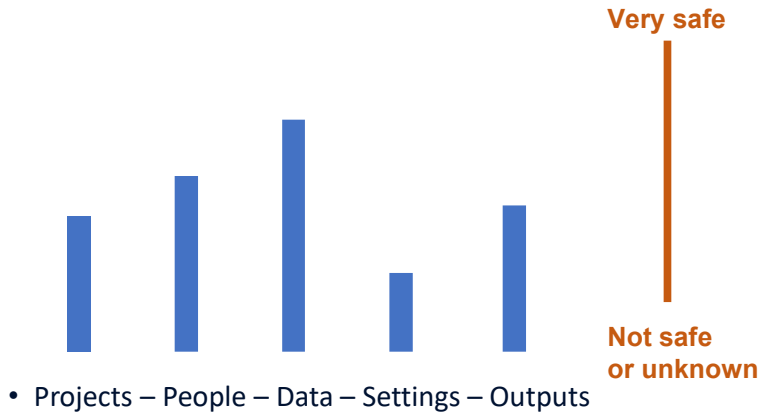
Highly treated  
Limited detail  
No identifiers  
Fully public

*Safe, low utility  
or even erroneous*

E.g., small toy or  
practice datasets

# CHALLENGES: DATA PROTECTION

• FIVE SAFES FRAMEWORK



**Scientific Use File**  
 Sampled & lightly treated  
 Some detail omitted  
 No identifiers  
 Screen & vet users

*Good analytical power,  
 some usage barriers*

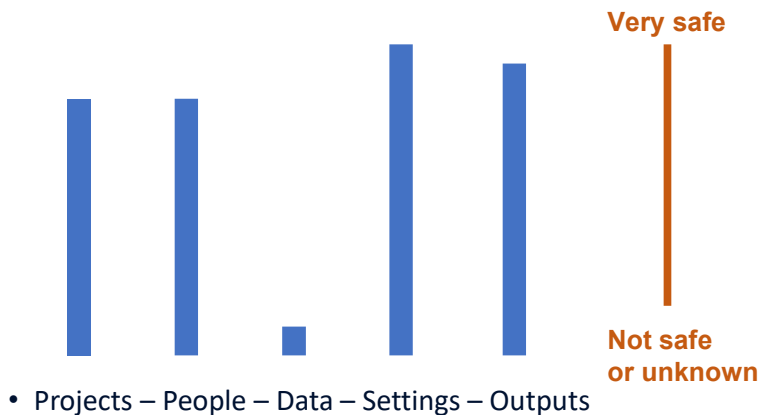
E.g., **IPUMS!** Also DHS,  
 MICS, most surveys

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# CHALLENGES: DATA PROTECTION

• FIVE SAFES FRAMEWORK



**Restricted centers**  
 Little or no infused error  
 Lots of detail & full files  
 May have identifiers  
 Detailed user application

*Great analytical power,  
 limited usage, costly*

E.g., Restricted access  
 data centers

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# CHALLENGES: DATA PROTECTION

• FIVE SAFES FRAMEWORK

- Projects – People – Data – Settings – Outputs



Very safe  
Not safe or unknown

**Controlled output systems**

Constrained flexibility  
Controlled detail  
For predictable outputs  
Public or internal users

*Retain controlled detail,  
limited flexibility*

E.g., Tabulators or in-house admin data query systems

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# CHALLENGES: DATA PROTECTION

**FIVE SAFES FRAMEWORK**

- Projects – People – Data – Settings – Output



**Extra safe data**

Highly treated  
Limited detail  
No identifiers  
Fully public

*Safe, low utility  
or even erroneous*

E.g., small toy or practice datasets

**Safe data-projects-people**

Sampled & lightly treated  
Some detail omitted  
No identifiers  
Screen & vet users

*Good analytical power,  
some usage barriers*

E.g., **IPUMS!** Also DHS, MICS, most surveys

**Safe people & settings**

Little or no infused error  
Lots of detail & full files  
May have identifiers  
Detailed user application

*Great analytical power,  
limited usage, costly*

E.g., Restricted access data centers

**Controlled output systems**

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# Confidentialization and disclosure control:

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IPUMS Treatments: Sampling, Suppression, Swapping

Codeshare Demo

# Confidentialization and disclosure control: Treatments

ST/ESA/STAT/SER.M/67/Rev.3

Department of Economic and Social Affairs  
Statistics Division

## Principles and Recommendations for Population and Housing Censuses

3.335. As presented in this subsection, there are methods (such as sampling, introduction of random disturbances, recoding and aggregation) that can be used to make such microdata available while still protecting individuals' rights to privacy. All have in common the fact that they sacrifice some information in order to eliminate or greatly reduce the risk of disclosure. However, it is important that census organizations interested in disseminating microdata to outside users should take the appropriate precautions to protect privacy and confidentiality.

Revision 3



# Confidentialization and disclosure control: Data Treatments

- Purpose: To modulate risk and utility; **to add uncertainty to data**
- In general datasets with:
  - **Many records and few variables will have inherently low risk due to the small chance of individuation of records.**
  - **Conversely, many variables and few records will result in a high number of unique cases - a potential risk.**
- In general data treatments:
  - **Remove information:** to limit risk but often also limit utility
  - **Add information:** Some treatments add noise/confusion, lowering risk while maintaining utility.

# Confidentialization and disclosure control: Treatments

Sampling

Introduction of random disturbances (noise)

Swapping

Shuffling

Perturbing

Suppression

Recoding and aggregation



# Confidentialization and disclosure control:

Intro

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Types of Data Treatments

**IPUMS Treatments:** Sampling, Suppression, Swapping

Codeshare Demo

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# Sampling

- All modern IPUMS International datasets are samples
- Samples drawn by NSO or IPUMS
- IPUMS provides systematic 1-in-10 sample when possible

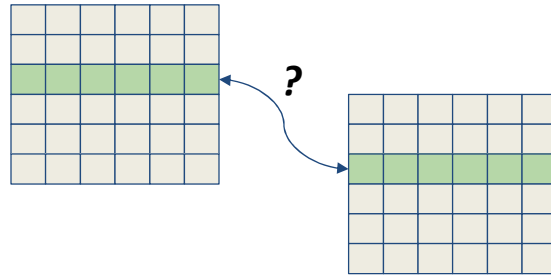
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# Sampling as disclosure control

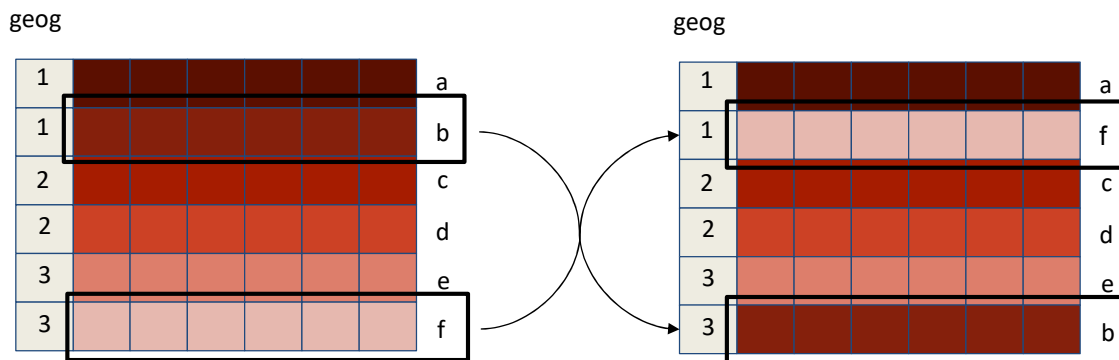
Sampling creates uncertainty:

Is a *sample* unique  
a *population*  
unique?



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# Random disturbance: Swapping

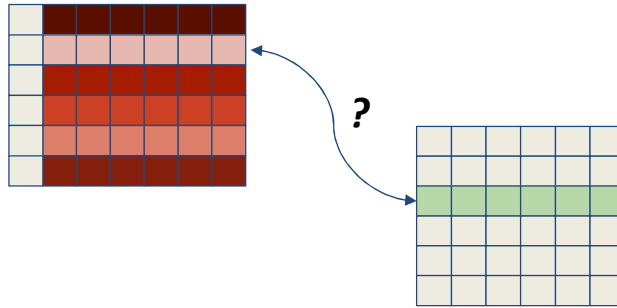


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# Swapping as disclosure control

Swapping creates uncertainty:

Is geography accurate for this particular record?



# Suppression

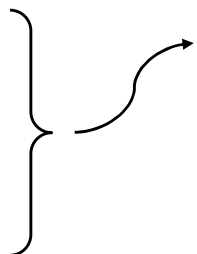
occupation	count
...	...
Statisticians	51
Mathematicians	18
Chemists	33
...	...

occupation	count
...	...
Statisticians and mathematicians	69
Chemists	33
...	...

# Suppression: Top/bottom coding

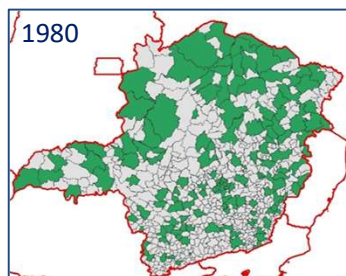
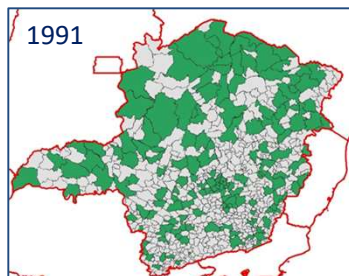
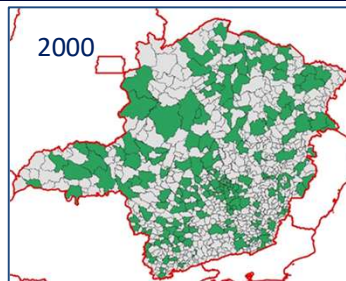
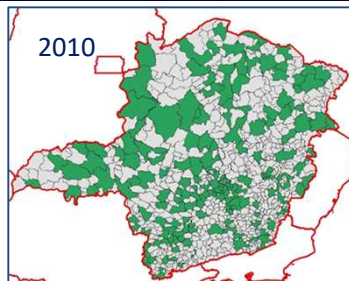
number_of_rooms	count
...	...
20	47
21	21
22	26
23	9

number_of_rooms	count
...	...
20+	103



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## Regional Confidentialization



Brazil  
**1980 - 2010**

Minas Gerais  
over the  
years

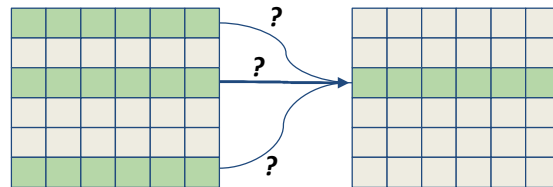
< 20,000 people	
2010	673 (79%)
2000	688 (81%)
1991	580 (78%)
1980	565 (80%)



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# Suppression as disclosure control

Suppression reduces uniqueness: Sample uniques are rarer



## CHALLENGES: DATA PROTECTION

### FIVE SAFES FRAMEWORK

- Projects – People – Data – Settings – Outputs



Very safe

Not safe or unknown

#### Scientific Use File

Sampled & lightly treated  
Some detail omitted  
No identifiers  
Screen & vet users


*Good analytical power, some usage barriers*

E.g., **IPUMS!** Also DHS, MICS, most surveys

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**CHALLENGES:  
DATA PROTECTION**

**FIVE SAFES FRAMEWORK**



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<https://www.abs.gov.au/about/data-services/data-confidentiality-guide/five-safes-framework>

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## Confidentialization and disclosure control:

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Risk and Utility Assessment

Types of Data Treatments

IPUMS-Specific Data Treatments

**Codeshare Demo**

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# Inspect Data

```

> ex_data
# A tibble: 26,624 x 19
  SERIAL new_geo0 new_geo1 new_geo2 new_geoFULL URBAN PERNUM nper RELATE AGE SEX MARST BIRTHYR BIRTHMO CITIZEN NATION EDATTAIN
  <dbl> <chr> <dbl> <dbl> <chr> <dbl> <dbl> <dbl><lbl> <dbl><L> <dbl><L> <dbl><L><L> <dbl><L><L> <dbl><L> <dbl><L><L> <dbl><L><L><L>
1 1 01 1 1 0111 RURAL 1 6 1 [HEAD] 45 [45] 1 [Mal.. 210 [Mar.. 1955 [195.. 4 [Apr.. 1 [Cit.. 13040 [Mor.. 120 [Som..
2 1 01 1 1 0111 RURAL 2 6 2 [SPOUSE/PARTN.. 48 [48] 2 [Fem.. 210 [Mar.. 1952 [195.. 8 [Aug.. 1 [Cit.. 13040 [Mor.. 110 [No ...
3 1 01 1 1 0111 RURAL 3 6 3 [CHILD] 18 [18] 2 [Fem.. 100 [SIN.. 1982 [198.. 1 [Jan.. 1 [Cit.. 13040 [Mor.. 221 [Gen..
4 1 01 1 1 0111 RURAL 4 6 3 [CHILD] 16 [16] 1 [Mal.. 100 [SIN.. 1984 [198.. 5 [May] 1 [Cit.. 13040 [Mor.. 212 [Pri..
5 1 01 1 1 0111 RURAL 5 6 3 [CHILD] 14 [14] 2 [Fem.. 100 [SIN.. 1986 [198.. 5 [May] 1 [Cit.. 13040 [Mor.. 110 [No ...
6 1 01 1 1 0111 RURAL 6 6 3 [CHILD] 12 [12] 2 [Fem.. 100 [SIN.. 1988 [198.. 12 [Dec.. 1 [Cit.. 13040 [Mor.. 120 [Som..
7 2 01 1 1 0111 RURAL 1 8 1 [HEAD] 48 [48] 1 [Mal.. 210 [Mar.. 1952 [195.. 7 [Jul.. 1 [Cit.. 13040 [Mor.. 312 [Som..
8 2 01 1 1 0111 RURAL 2 8 2 [SPOUSE/PARTN.. 43 [43] 2 [Fem.. 210 [Mar.. 1957 [195.. 2 [Feb.. 1 [Cit.. 13040 [Mor.. 110 [No ...
9 2 01 1 1 0111 RURAL 3 8 3 [CHILD] 17 [17] 1 [Mal.. 100 [SIN.. 1983 [198.. 11 [Nov.. 1 [Cit.. 13040 [Mor.. 311 [Gen..
10 2 01 1 1 0111 RURAL 4 8 3 [CHILD] 15 [15] 1 [Mal.. 100 [SIN.. 1985 [198.. 9 [Sep.. 1 [Cit.. 13040 [Mor.. 221 [Gen..
# i 26,614 more rows
# i 2 more variables: OCC <dbl><lbl>, DISABLED <dbl><lbl>
    
```

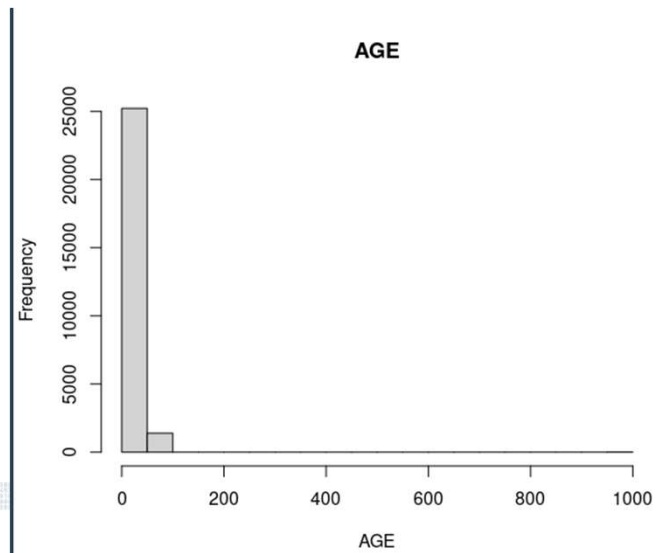
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# Inspect Variables

Labels:	value	label
	0	Less than 1 year
	1	1 year
	2	2 years
	3	3
	4	4
	5	5
	6	6
	7	7
	8	8
	9	9
	93	93
	94	94
	95	95
	96	96
	97	97
	98	98
	99	99
	100	100+
	999	Not reported/missing



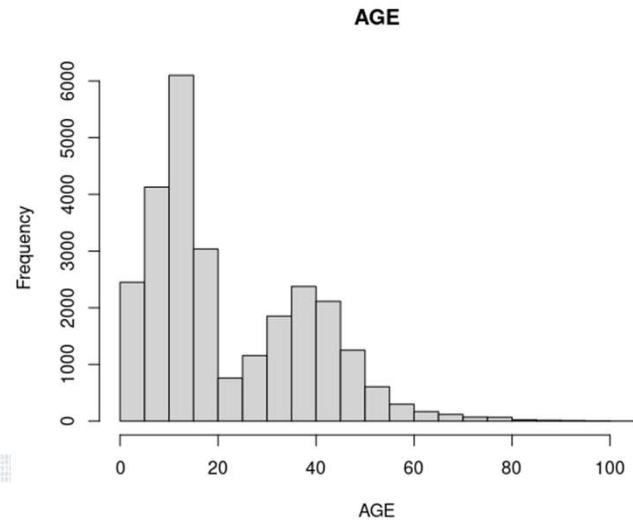
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# Inspect Variables - Recode Special Cases

- Recode Special Values
  - AGE

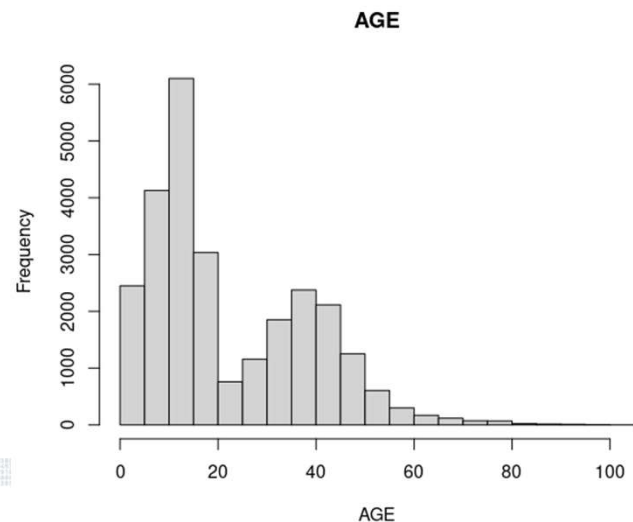
For cases when AGE ==999, set to NA
- ```
ex_data <- ex_data %>%  
mutate(AGE2 = if_else(AGE==999,  
NA_integer_, AGE))
```



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# Top-coding Age

- Skewed distributions of age can mean low-representation.
- Consider top-coding and/or grouping into 5-yr age cohorts
  - Raises utility for analysis
- IPUMS releases both a top-coded integer-age as well as a 5-yr age-group



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## Consider Related Variables

- Age: more than just age
  - If you top-code age, make sure to bottom-code Birth Year
- Other commonly related variables:
  - Country of birth/nationality
  - Occupation, industry, etc

## Detecting and Recoding of Small Cells

- Occupation has over 100 levels of responses, some highly represented, some very minimally represented.

# Recoding of Nationality/Citizenship

## References

Dupriez, Olivier and Ernie Boyko. 2010. "Dissemination of Microdata Files. Formulating Policies and Procedures", International Household Survey Network, IHSN Working Paper No 005.  
<http://ihsn.org/sites/default/files/resources/IHSN-WP005.pdf>

Hundepool, Anco, Josep Domingo-Ferrer, Luisa Franconi, Sarah Giessing, Rainer Lenz, Jane Naylor, Eric Schulte Nordholt, Giovanni Seri, and Peter-Paul De Wolf. 2010. *Handbook on Statistical Disclosure Control, version 1.2*. ESSNet SDC. [https://cross-legacy.ec.europa.eu/system/files/SDC\\_Handbook.pdf](https://cross-legacy.ec.europa.eu/system/files/SDC_Handbook.pdf)

# References

risk assessment:

sdcmicro User Guide: <https://sdcppractice.readthedocs.io/en/latest/intro.html>

sdcmicro is an R package produced by The World Bank, in collaboration with Intl Household Survey Network (IHSN), PARIS21 (OECD), Statistics Austria and the Vienna University of Technology.

k-anonymity:

Samarati, Pierangela; Sweeney, Latanya (1998). "Protecting privacy when disclosing information: k-anonymity and its enforcement through generalization and suppression" (PDF). Harvard Data Privacy Lab. Retrieved April 12, 2017.

critiques of k-anon and expansions (t-closeness):

N. Li, T. Li and S. Venkatasubramanian, "t-Closeness: Privacy Beyond k-Anonymity and l-Diversity," 2007 IEEE 23rd International Conference on Data Engineering, Istanbul, Turkey, 2007, pp. 106-115, doi: 10.1109/ICDE.2007.367856.

Utility Assessment: sdcmicro material and the synthpop team (Based at University of Edinburgh):

"Assessing, visualizing and improving the utility of synthetic data." Raab, G. UNECE CONFERENCE OF EUROPEAN STATISTICIANS:

Expert Meeting on Statistical Data Confidentiality

1-3 December 2021, Poland

[https://unece.org/sites/default/files/2021-12/SDC2021\\_Day2\\_Raab\\_AD.pdf](https://unece.org/sites/default/files/2021-12/SDC2021_Day2_Raab_AD.pdf)